Reinforcement Learning 2

Complications & approximations

Andrew Lampinen

Psych 209, Winter 2018

Introduction

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- Exploration & on/off-policy learning.
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- Other types of feedback.

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- Infinite spaces, approximation & generalization.
- Correlations & replay.
- Exploration & on/off-policy learning.
- Hierarchies & plans.
- Other types of feedback.
- Unobservables & POMDPs, different assumptions and other approaches.

Function approximation

Similarities & dissimilarities

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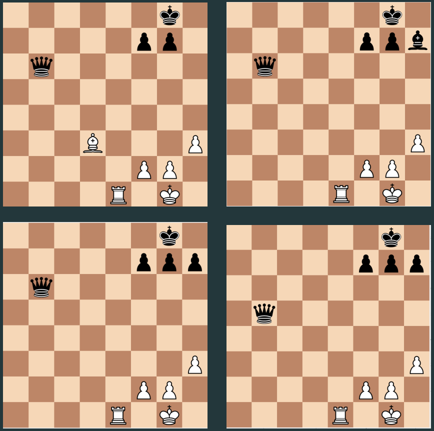
- More state, action pairs in chess than atoms in observable universe. However:



Approximating the Q-table

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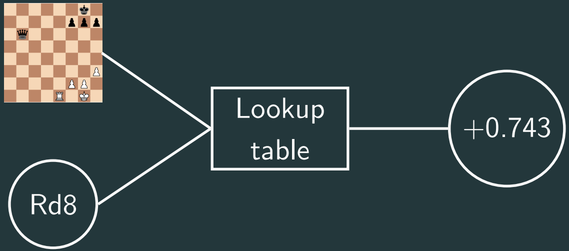

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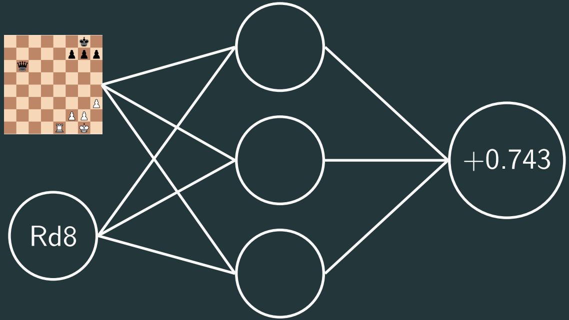

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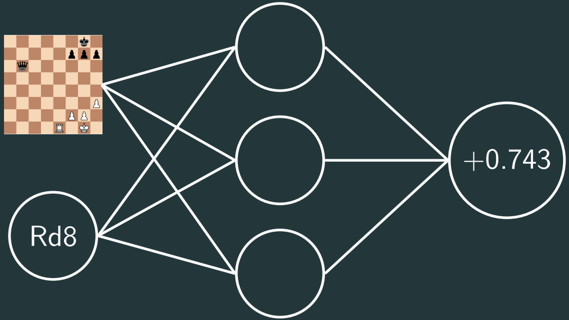
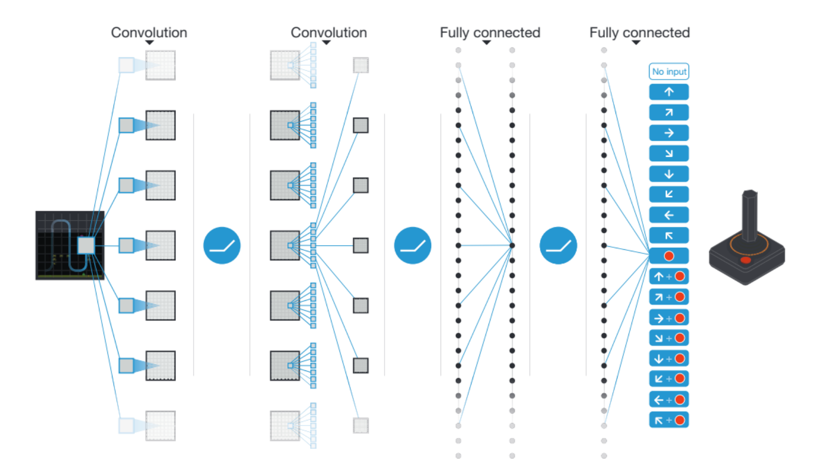


- Loss:

$$L = \left(r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a'; \theta_i^-) - Q(s_t, a_t; \theta_i) \right)^2$$

Playing atari games



Replay

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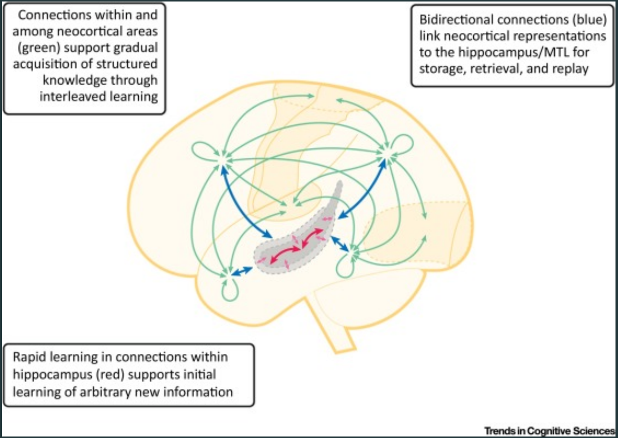
- CLS is a theory of how humans and animals avoid this:



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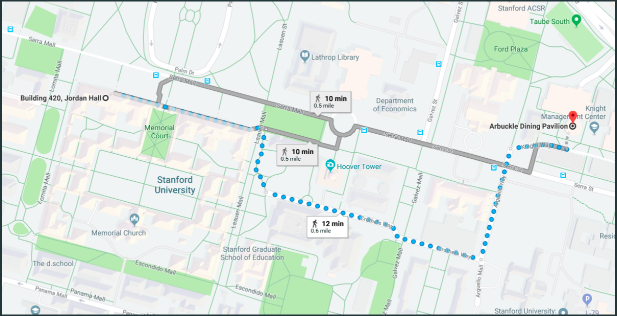
- ... and potentially replay many experience for each real world time step.

Exploration and exploitation and on/off policy

The need to explore



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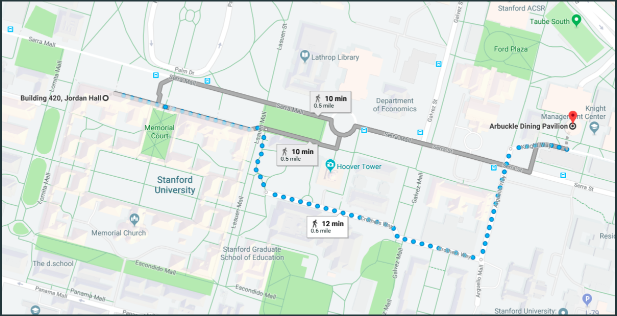

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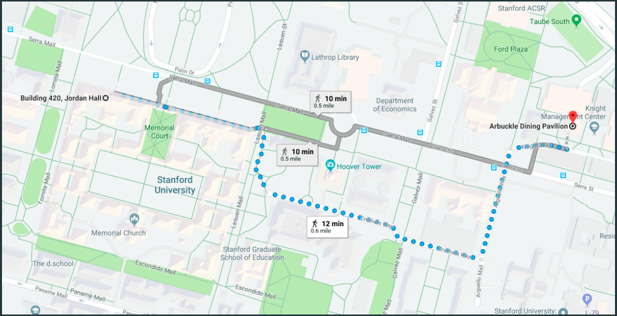

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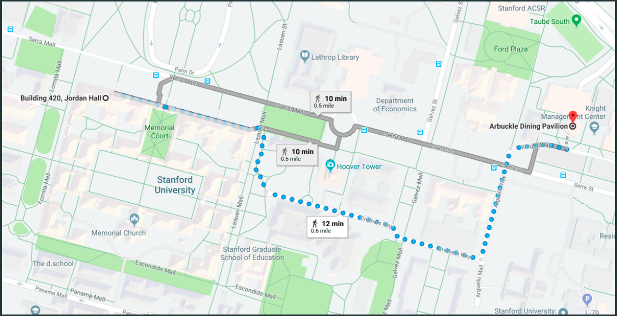

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- This is important – remember convergence guarantees required *every* state, action pair to be visited "frequently."

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- Exploiting risks missing a great opportunity.
- We have to find some balance between these that results in good payoffs but still makes sure we don't miss too much.

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- (There are other possibilities, e.g. using a softmax over Q values.)

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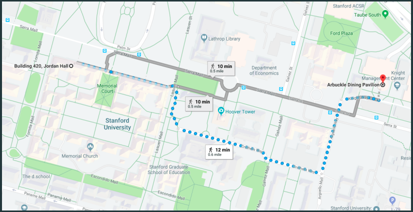
- Do chess players stop learning when they're playing for the world championship?
- A self-driving car can't just be trained and set free – destinations, roads, and laws are all evolving.
- What if my direct path to lunch was blocked by a building that was torn down?



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- If we want to behave optimally with a policy π that explores, we have to incorporate this policy into the learning rule:

$$\Delta Q^{\pi}(s_t, a_t) \stackrel{?}{=} \alpha\left(\left[r_{t+1} + \sum_{a'} p(a' | s_t, a_t, s_{t+1}, \pi)\, \gamma Q^{\pi}(s_{t+1}, a')\right] - Q(s_t, a_t)\right)$$

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- Since our actions in the state are distributed according to π, in expectation our Q-value updates will be as well.

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- **On-policy:** Can be faster, can be more stable.
- **Off-policy:** Can learn from anything, even totally random play. This makes incorporating replay or changing ϵ for more early exploration easier.

Hierarchies & plans

Plans = hierarchies of actions

Excercise to stay healthy

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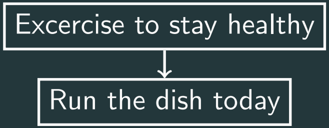


Plans = hierarchies of actions

Excercise to stay healthy

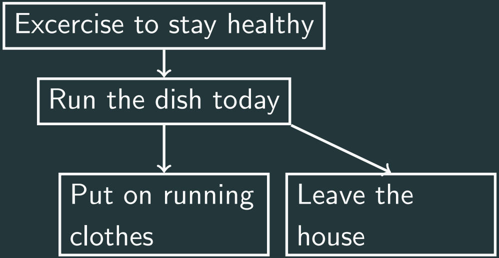
↓

Run the dish today

↓

Put on running clothes

Plans = hierarchies of actions



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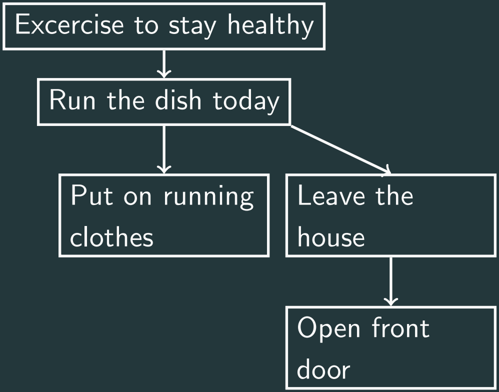

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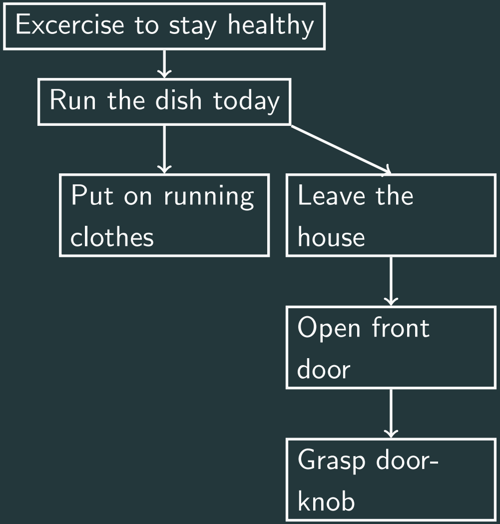

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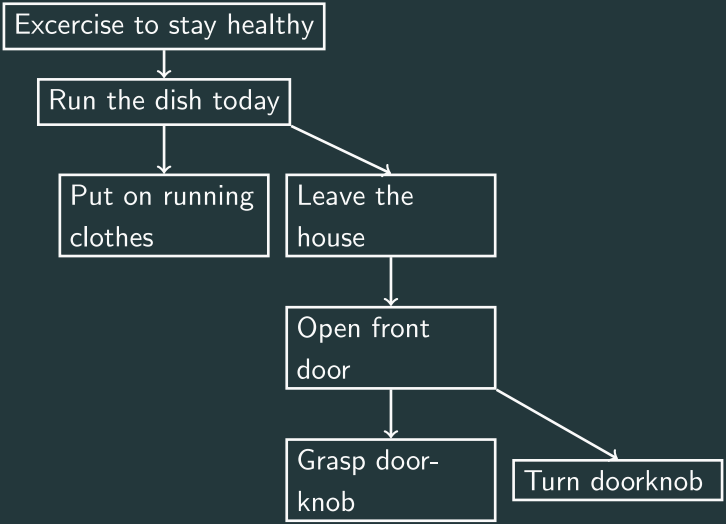

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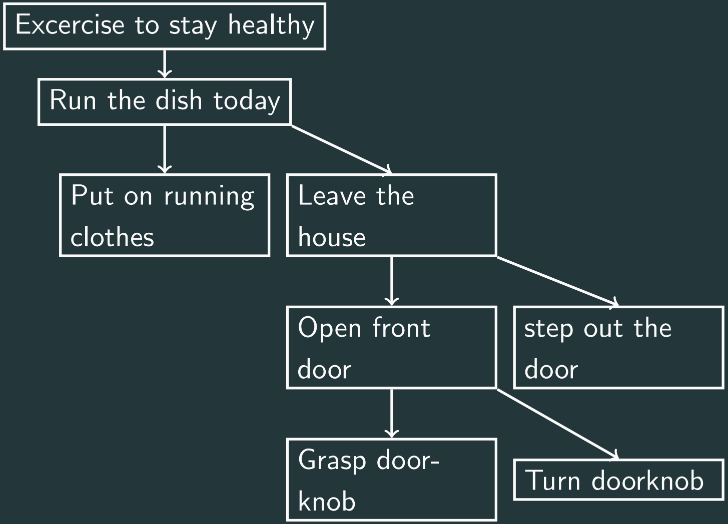

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- But how do you figure out what the higher level actions should be?
- Still an open problem (though there is work on it), and potentially a good project is to think about how some aspect of behavior could be explained this way, and what assumptions you would need to make it work!

Other types of feedback

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- May help with picking up on longer-term structure.
- Or with building relevant prior knowledge.

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- And much more.

Wrapping up

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- Can approximate Q using deep learning (for generalization).
- There's a trade-off between **exploring** and **exploiting**!
- ... and there's way more to RL than will fit on one slide or in one course.